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FINAL REPORT

ONR CONTRACT: N00014-88-K-0170
Principal Investigator: Shanti S. Gupta
Period of Report: February 1, 1988 – September 30, 1990

PURDUE UNIVERSITY

DEPARTMENT OF STATISTICS

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During the period under review, the research activities of the following members were supported for varying lengths of time: (1) Professor S. S. Gupta, (2) Professor S. Panchapakesan, (3) Professor TaChen Liang, (4) Professor K. J. Miescke, (5) Professor D. Y. Huang, (6) Professor L. Y. Leu, (7) Professor J. Shao, and (8) Professor B. Ya. Levit.

Also, during this period two graduate students, who have been working on their Ph.D. theses under the supervision of Professor Gupta, were supported at different times. These are: Sayaji N. Hande and Yuning Liao.

Professor Gupta presented invited papers and gave invited lectures at several international conferences and professional meetings abroad with partial or full support for travel from the Office of Naval Research. These are: Indo-U.S. Workshop on Bayesian Analysis in Statistics and Econometrics, Bangalore, India (December 1988); International Symposium on Probability, Statistics and Experimental Designs, New Delhi, India (December 1988); International Workshop on Linear Models, Experimental Designs, and Related Matrix Theory, Tampere, Finland (August 1990); and the Joint Bernoulli World Congress and 53rd Annual Meetings of the Institute of Mathematical Statistics.

The research of the several investigators supported on this contract mainly pertains to the area of statistical selection and ranking theory dealing with several situations of interest in statistical analyses, decision-making, reliability and quality control. A summary of significant accomplishments is given in Part I below, followed by a listing (Part II) of books, published papers, and yet unpublished technical reports relating to the entire period of this contract.

PART I: SUMMARY OF SIGNIFICANT ACCOMPLISHMENTS

The important results of the research carried out under the contract deal with several aspects of multiple decision (ranking and selection) and related problems. A substantial part of these results relate to Bayes and empirical Bayes procedures. Some interesting results have also been obtained in the area of simultaneous estimation and selection problems. Of wide interest in applications are results involving binomial, multinomial, lognormal, logistic, and Tukey's lambda distributions. All these and other significant accomplishments under the contract are presented below.

1. Introduction

Methodologies for selecting and ranking (ordering) populations were developed to provide experimenters with meaningful statistical formulations for real-life problems that often had been inappropriately posed and inadequately analyzed as tests of homogeneity. The basic setup for these problems can be briefly stated as follows.

Let $\pi_1, \pi_2, \ldots, \pi_k$ be k populations where π_i is described by the probability space $(\mathcal{X}, \mathcal{B}, P_i)$ where P_i belongs to some family $\mathcal{P}$ of probability measures. We assume that there is a partial order relation ($\succ$) defined in $\mathcal{P}$ so that $P_i \succ P_j$ (or equivalently, $\pi_i \succ \pi_j$) denotes the fact that π_i is better than π_j. For example, if $\mathcal{P}$ is a one-parameter family $P_i(x) = P(x, \theta_i)$, where θ_i is real-valued, we may define $P_i \succ P_j$ if and only if $\theta_i \geq \theta_j$. We assume, in the general setup, that there exists a population π_j such that $\pi_j \succ \pi_i$ for all i. This population is referred to as the *best* population. In case of more than one such population we consider one of them to be tagged as the best; this is done for mathematical convenience. The goal of the experimenter is to select the best. The multiple decision (ranking and selection) problems have been studied by several investigators under one of two formulations. now commonly known as the indifference zone formulation [due to Bechhofer, (1954)*] and the (random size) subset selection formulation. Significant initial

*The references cited by years are listed at the end of this part.

contributions to the subset selection have been made by Gupta (1956, 1963, 1965) and, Gupta and Sobel (1958, 1960, 1962). During all these subsequent years, the research in the area of selection and ranking in general has been very prolific and has made an impact on the growth of statistical literature. Significant contributions to the subset selection theory have been continually made all these years by Professor Gupta, his students and collaborators. A review of these developments over thirty years and an assessment of the impact of these developments on users have been given by Gupta and Panchapakesan (1985).

Significant results of our investigations described below are grouped under different topics that highlight their importance.

2. Bayes and empirical Bayes Procedures

Bayes procedures are appropriate when the experimenter has some prior information about the parameters of interest which can be expressed in the form of a prior distribution. Initial contributions have been made to selection and ranking using Bayesian approach notably by Deely and Gupta (1968), Bickel and Yahav (1977), Chernoff and Yahav (1977), Goel and Rubin (1977), and Gupta and Hsu (1978).

It is not always possible to assume a known prior distribution for the parameters of interest. In situations where one is repeatedly confronted with the same selection problem independently, it is reasonable to formulate the component problem in the sequence as a Bayes decision problem with respect to an unknown prior distribution on the parameter space, and then use the accumulated observations to improve the decision at each stage. This is the empirical Bayes approach due to Robbins (1956, 1964). It is also known as nonparametric empirical Bayes approach to distinguish it from the so-called parametric empirical Bayes approach in which the parameters are assumed to have a prior distribution involving unknown hyperparameters. Recent contributions in this direction have been made by Gupta and Liang (1986, 1988).

Gupta and Liang [A6]* obtained two-stage allocation procedures for selecting the population with the largest mean from several normal populations having a common known variance. Assuming that the unknown means θ_i have a known normal prior $N(\theta_0, \tau^2)$, an exact two-stage allocation procedure was derived under a linear loss. However, this allocation procedure cannot be used when τ^2 is unknown. In this case, Gupta and Liang [A6]* have proposed an adaptive two-stage allocation procedure based on an empirical Bayes approach and have established its asymptotic optimality in terms of convergence rate.

Deely and Gupta [C1] have adopted a hierarchical Bayesian model and derived procedures for selecting the best of k binomial parameters, say, the success probabilities corresponding to k different suppliers. The hierarchical model facilitates the use of any prior information in the analysis for samples of both large and small sizes. In addition to computing posterior probability that the i^{th} supplier is the best, $i = 1, \ldots, k$, Deely and Gupta [C1] have derived expressions for deciding how much better a given supplier is relative to the others. Prior information is assumed to begin with exchangeability. The prior can be more informative if the experimenter has other knowledge about the suppliers as a group.

Gupta and Liang [A5] studied the problem of selecting the best population from several binomial populations. Let $\underline{p} = (p_1, \ldots, p_k)$, where p_i is the probability of a success in the i^{th} population. Let $p_{[k]} = \max_{1 \leq i \leq k} p_i$. The population associated with $p_{[k]}$ is called the best population. Under the linear loss $L(\underline{p}, i) = p_{[k]} - p_i$, where i is the index of the selected population, this statistical problem has been studied via a parametric empirical Bayes approach. It is assumed that the binomial parameters $p_i, i = 1, \ldots, k$, follow conjugate beta prior distributions with unknown hyperparameters. Under this framework, an empirical Bayes selection procedure has been proposed and it is shown that the Bayes risk of this

*The references cited by numbers such as [A6] are listed in Part II.

empirical Bayes procedure converges to the corresponding minimum Bayes risk with rate of convergence of order $O(\exp(-cn))$ for some positive constant c, where n is the number of accumulated past observations at hand.

Gupta and Liang [B6] have also studied the problem of selecting good negative binomial populations as compared with a standard or a control using a nonparametric empirical Bayes approach. First, monotone empirical Bayes estimators of the parameters were derived. Based on these estimators, monotone empirical Bayes selection procedures were constructed. Asymptotic optimality properties of the above estimators and selection procedures were also investigated. The respective convergence rates for estimations and the selection problems have been obtained, under certain conditions. Liang [C14] investigated the parallel problem of selecting the negative binomial population with the highest probability of success using the nonparametric empirical Bayes approach.

Gupta and Liang [C7] studied an empirical Bayes procedure for selecting fair multinomial populations relative to a standard. Let $p_i = (p_{i1}, \ldots, p_{im})$ denote the cell-probability vector of a multinomial distribution in m cells, $i = 1, \ldots, k$. Define $\theta_i = \sum_{j=1}^{m} (p_{ij} - \frac{1}{m})^2$, which is a measure of the uniformity among the cells of π_i. It is essentially equivalent to the Gini-Simpson index. For a given $\theta_0, 0 < \theta_0 < 1 - \frac{1}{m}$, popuiation π_i is defined to be fair if $\theta_i \leq \theta_0$ and bad otherwise. Gupta and Leu assumed a loss function which is the sum of losses due all misclassified populations. Loss for misclassifying π_i is $|\theta_i - \theta_0|$. They have proposed an empirical Bayes procedure for selecting all the fair populations, and showed that their procedure is asymptotically optimal relative to a class of symmetric Dirichlet priors. They have shown the rate of convergence of the risk of the empirical Bayes procedure to the minimum Bayes risk is of order $O(\exp(-\tau k + \ell n\ k))$ for some positive constant τ, where k is the number of populations.

3. Classical Procedures for Specific Distribution Models

Gupta and Han [B2] have investigated a two-stage procedure for selecting the population with the largest mean from among k logistic populations. Based on Edgeworth series expansions, they have derived a formula for the distribution of sample means. Using this result, an elimination-type two-stage selection procedure based on the sample means has been investigated for the case when the logistic distributions have a common known variance. A table of constants necessary to implement this procedure has been provided by Gupta and Han and its efficiency relative to the single-stage procedure has been investigated.

For k lognormal populations differing only in a certain parameter θ, Gupta and Miescke [A7] considered the problem of selecting the population with the largest value of θ. For two-parameter lognormal families the problem is solved for several natural choices of θ by using logarithmic transformation of the observations and estimation of parameters in possibly restricted normal populations. For three-parameter lognormal families, this standard approach of selecting in terms of natural estimators fails if θ is the "guaranteed lifetime." For this case, a selection procedure was derived by Gupta and Miescke [A7] using an L-statistic with the smallest asymptotic variance. Comparisons were made with other suitable selection rules and the new rule was found to compare favorably with others.

Gupta and Sohn [B9] have studied selection from Tukey's generalized symmetric lambda distributions with different unknown location parameters and common known scale and shape parameters. They proposed and studied a procedure based on sample medians for selecting a subset containing the population with the largest location parameter. The importance of this study lies in the fact that the lambda distribution can be used to approximate many continuous distributions. Also, the lambda family of distributions is simple, flexible and easy to use. This enhances the potential of the procedures for the lambda family in practical applications because convenient softwares can be prepared which can give good approximate results for several parametric families of distributions. Gupta and Leu [A3] investigated the problem of selecting, from $k(\geq 2)$ m-sided dice, the fairest die, i.e., the die associated with the smallest $\theta_i = \sum_{j=1}^{m}(p_{ij} - \frac{1}{m})^2$, where the p_{ij} are the face probabilities of the i^{th} die. They proposed subset selection procedures based on Schur-convex functions. For small sample cases, conservative solution for finding the selection constant is given. They have also studied the related problem of selecting a subset containing good populations, i.e., those for which $\theta_i \leq \theta_0$, a prespecified constant such that $0 < \theta_0 < 1 - \frac{1}{m}$. Gupta and Liang [C7], who investigated an empirical Bayes procedure for the same problem, have shown that, for their loss function, the natural procedure of Gupta and Leu is Bayes relative to a symmetric Dirichlet prior and consequently is admissible.

4. Isotonic Selection with Respect to A Control

Let $\pi_1, \ldots, \pi_k$ be k populations (experimental treatments) and π_0 be a control population. Let π_i have a distribution F_{θ_i}, $i = 0, 1, \ldots, k$. The control parameter θ_0 may or may not be known. The parameters θ_i, $i = 1, \ldots, k$, are unknown. Selecting the experimental treatments that are better than the control (i.e. those π_i's for which $\theta_i \geq \theta_0$) has been considered in the early literature assuming that there is no information about the ordering of the experimental parameters. However, there are situations like experiments involving different dose levels of a drug, where it is reasonable to assume that $\theta_1 \leq \theta_2 \leq \ldots \theta_k$ even though we may not know the values of these θ_i. Under this assumption, Gupta and Huang (1982), and Gupta and Yang (1984) studied isotonic selection rules in the classical setup. The isotonic selection rules are based on isotonic estimators of the ordered parameters $\theta_1 \leq \ldots \leq \theta_k$ and have the isotonic property: If a population associated with θ_i is selected, then any population with parameter $\theta_j > \theta_i$ is also selected. Gupta and Huang (1982) investigated the case of binomial populations with success probabilities θ_i, and Gupta and Yang (1984) studied the case of normal means θ_i (common variance σ^2 may be known or unknown).

Using the classical approach, Gupta and Sohn [C5] studied the case of Tukey's generalized symmetric lambda distributions, where the comparison is in terms of the location parameters θ_i assuming that all populations have common known scale and shape parameters. Their procedure is based on isotonized sample medians.

Liang and Panchapakesan [C8] derived a Bayes rule under a fairly general loss function assuming θ_0 to be known. They have also discussed applications to discrete (with Poisson as an example) as well as continuous exponential class of distributions.

5. Sequential Selection Procedures

The problem of selecting the best population based on a sequential subset selection approach has been studied by Gupta and Liang [B5] and Liang [C13]. The goal is to select a small subset such that the best population is included in the selected subset and any other selected population is "close" to the best population. The selection procedures of Gupta and Liang [B5] are based on an invariant statistic for the parameters of interest. They consider observation from each pair of k populations and perform a modified sequential probability ratio test (MSPRT) based on the invariant statistics. This is done simultaneously for all pairs of populations and if a particular MSPRT terminates, then an appropriate corresponding population is removed from the set of contenders for the best. This is continued until only one population belongs to this set or the statistical evidence indicates that all the populations remaining in this set are within a (small) specified distance from the unknown best population. At each stage, the selection procedure also provides some statistical inference about an upper bound on the measure of separation between the unknown best and each remaining population. Liang [C13] considered the same selection goal and studied a sequential selection procedure for the exponential family distributions. He considered an appropriate transformation of the random observations taken from any two populations. With this transformation, the likelihood function of the new statistics can be factored into two parts, one of which obtained by a conditional argument and termed the conditional likelihood function, is a function only of the parameter of interest. Based on the conditional likelihood function, a sequential subset selection procedure is derived. This sequential subset selection procedure has similar properties as that of Gupta and Liang [B5].

Gupta and Panchapakesan [B8] provided a review of the recent developments of sequential selection procedures. The paper [B8] describes some sequential selection procedure, for selecting the normal population having the largest mean, and for the Bernoulli population having the largest success probability. Both indifference-zone and subset selection results are discussed.

6. Lower Confidence Bounds for PCS and Estimating the Mean of the Selected Population

For the problem of selecting the best of several populations using the indifference-zone formulation, a natural rule is to select the population yielding the largest sample value of an appropriate statistic. For this approach, it is required that the experimenter specify a number δ^*, say, which is a lower bound on the difference between the largest and the second largest parameter. However, in many situations, it is hard to specify the value of δ^*, and therefore, the probability of a correct selection cannot be guaranteed to be at least P^*, a prespecified probability level. Gupta and Liang [B4] have studied the problem of deriving a lower confidence bound for the probability of a correct selection for the general location model $F(x - \theta_i)$, $i = 1, \ldots, k$. First, they derive simultaneous lower confidence bounds on the differences between the best and each of the other non-best population parameters. Based on these, they obtain a lower confidence bound for the probability of a correct selection. The general result is then applied to the selection of the best mean of k normal populations with both the known and unknown common variances. In the first case one needs a single-stage procedure while in the second case a two-stage procedure is required. Some simulation investigations were carried out and their results were provided.

Gupta, Leu and Liang [A4] studied the problem of deriving lower confidence bounds for the probability of a correct selection in truncated location-parameter models. Two cases were considered according to whether the scale parameter is known or unknown. For each case, a lower confidence bound for the difference between the best and the second best was obtained. These lower confidence bounds were then used to construct lower confidence bounds for the probability of a correct selection. The results were then applied to the problem of selecting the best exponential population having the largest truncated location-parameter. Useful tables were provided for implementing the proposed methods.

In many practical situations, an experimenter may not just want to find out the population with the largest mean, but also would like to know how good the selected population is. Almost all results in the vast literature on ranking and selection are restricted to one of the two decision problems. Cohen and Sackrowitz (1988) presented a decision-theoretic framework for the combined decision problem and derived results for the case of two normal populations with equal sample sizes. In [B6], Gupta and Miescke studied the problem of selecting the population with the largest mean from among $k(\geq 2)$ normal populations and simultaneously estimating the mean of the selected population in the decision-theoretic approach. Under several loss functions with two additive components, due to selection and estimation, Bayes rules were derived and studied. The cases of both equal and unequal sample sizes are treated. The "natural" rule, which selects in terms of the largest sample mean and then estimates with the sample mean of the selected population, was critically examined in all situations considered. In another paper [C9], Gupta and Miescke considered a similar problem for binomial populations. Under several loss functions, they have derived Bayes decision rules assuming independent beta priors. A fixed sample size look ahead procedure was also considered.

7. Miscellaneous Topics

In [A2], Gupta and Huang investigated the problem of selecting important independent variables in linear regression models using the subset selection approach. The technique developed in this paper provides a guaranteed probability of correctly selecting the best set of regression variables. In [C4], the same problem was investigated using the influence diagnostics. The criterion for selecting the important variables turns out to be the same as in [A2].

Leu and Liang [A9] studied the problem of selecting the best population from among k two-parameter exponential populations. They proposed new selection procedures which include preliminary tests thus allowing the experimenter to have the option not to select if the test is not significant. The probability of making a selection as well as the probability of a correct selection are controlled. In another paper [B3], Gupta, Leu, and Liang proposed similar procedures in the case of populations which are location-scale models. Specifically, the normal unknown means problem was studied. Comparisons between the proposed and the earlier existing procedures were carried out.

Gupta and Liao [C8] investigated the classical and Bayes-P^* selection procedures for double exponential (Laplace) populations. Under a noninformative prior, the relation between the classical maximum-type and the Bayes-P^* procedure was studied. An improved lower bound for the guaranteed probability of a correct selection was obtained.

In [C3], Gupta and Hande studied the selection and ranking problem in a nonparametric setup when the populations are ranked in terms of a suitably defined functional of the distribution functions. Both indifference zone and subset selection formulations were studied. Approximate nonrandomized rules were obtained for each case. Some relevant simulation studied were carried out. These studied indicate that the nonrandomized version of the nonparametric procedure performs better when the associated distribution functions are stochastically increasing in the parameters.

In [A9], Liang investigated the convergence rates of a sequence of monotone Bayes tests for the two-action decision problems for uniform distributions. It was shown that the sequence of monotone empirical Bayes tests is asymptotically optimal. In another paper [A10], Liang investigated the problem of estimating the binomial parameter via the nonparametric empirical Bayes approach. Assuming symmetric priors, a monotone empirical Bayes estimator was constructed by using isotonic regression. This estimator was shown to be asymptotically optimal in the usual empirical Bayes sense.

In [B1], Gupta and Balakrishnan studied the properties of order statistics from a logistic distribution. Several aspects discussed include: percentiles and modes, exact and explicit expressions for the single and the product moments of order statistics, recurrence relations for single and product moments, and relations between moments for the case of a doubly truncated logistic distribution.

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Part II: Publications Supported by Contract

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C. Unpublished Technical Reports: Submitted or to be Submitted for Publications

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